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A PATTERN RECOGNITION STUDY OF THE INFLUENCE OF MATERIAL PROPERTIES ON THE PREDICTION OF CRATER GEOMETRIES

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The pattern recognition code ARTHUR was tested on a limited cratering data base to examine its utility in studying complex continuous data. The code was found to be a convenient data analysis package but possessed no continuous data capability that is not already available to any researcher.

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PREFACE

In a feasibility study of this type, many people contributed to this effort. Dr. J. Alexander assisted in the code conversion. Dr. J. Masso suggested many programming techniques used in this study. The help of these and other S^3 employees is greatly appreciated.

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I. INTRODUCTION

Systems, Science and Software (S^3) has conducted a feasibility study of the use of pattern recognition techniques to determine the influence of material properties on crater geometries. The computer code entitled ARTHUR [1] was acquired and made operational on the S^3 UNIVAC 1100/81. This pattern recognition code was then applied to a limited cratering data base taken from the work of Dillon. [2]

It was the purpose of this study to determine if pattern recognition techniques contained in the ARTHUR code were useful for studying cratering systematics of the Dillon data base, and whether these techniques ought to be applied to a larger and more diverse data set. The data consisted of information for 196 high explosive (HE) and 10 nuclear explosive (NE) craters. The test sites are in eight (8) different media representing a total density range of .96 to 2.72 g/cc. The HE event yields varied from 1 to 1 million pounds of TNT, and the NE events range from .085 to 100 KT. Dillon used this data to produce formulas by regression analysis for crater radius, depth and volume as functions of scaled DOB and yield. Table 1 summarizes the important features of the data. [2]

The general problem in the study of crater systematics is to determine from a finite set of cratering data the influence of the measurable features of cratering event (the material properties of the site and the type and emplacement of the explosive source) on the observed geometry of the crater (volume, radius and depth). Having established these systematic effects in a sufficiently precise and quantitative form, one can then reliably predict the geometry of some contemplated crater. The near linear relation between explosive yield and crater volume has long been recognized. The systematic variation of cratering efficiency (crater volume per unit energy of the explosive source) and gross material category is

TABLE 1

A) HE Craters

Medium	Below Ground	Surface Burst
Alluvium	69	3
Playa	39	17
Sand	29	3
Basalt	16	5
Shale	8	-
Tuff	5	-
Rhyolite	1	-
Limestone	1	-

B) NE Craters

Medium	Total
Alluvium	5
Basalt	2
Rhyolite	2
Tuff	1

C) Yield

Kg HE	Total	KT NE	Total
.1 - 1	53	10^{-2} - 10^{-1}	1
1 - 10	24	10^{-1} - 10^{0}	2
10 - 10^2	4	10^{0} - 10^{1}	5
10^2 - 10^3	86	10^{1} - 10^{2}	2
10^3 - 10^4	8		
10^4 - 10^5	20		
10^5 - 10^6	1		

also well known. For the same energy release and source emplacement, craters in wet, weakly cohesive materials are much larger than in hard rock. The effect of water table and geologic layering of the crater site has also been studied.[3, 4, 5] The larger cratering efficiency of high explosive sources (HE) compared to nuclear explosive sources (NE) has also been established.[3] The object of this feasibility study was to examine the ability of pattern recognition techniques, in particular the ARTHUR code, to extend the known correlations to include finer detail concerning the site material properties.

The Dillon analysis is a natural benchmark for this study, but we would like to do better than fit to an arbitrary functional form which may be a poor representation of reality. Thus one question addressed in this study is whether ARTHUR possesses any special features which clarify the data structure, and make possible more physically realistic fits. A second question is whether the techniques in ARTHUR are simpler to use or more refined than more conventional data analysis packages.

The various techniques in ARTHUR and their relevance to the cratering systematics problem are discussed in Section II. Section III presents the results of ARTHUR applied to the Dillon data base. Section IV reports a more successful application of ARTHUR to data on the strength of tuff. The conclusion is presented in Section V, and a general discussion of ARTHUR and pattern recognition is presented in the Appendix.

II. ARTHUR TECHNIQUES

The ARTHUR code has twenty-six (26) "verbs", or control words, which trigger the various data handling or data analysis techniques. In this section each of these techniques will be discussed briefly. Of particular interest is whether the technique is applicable to discrete (category) or continuous properties.

In the cratering analysis problem the "property" of interest is a continuous variable such as the crater volume. Thus, only continuous property techniques will be applicable.

It will be seen that a large majority of the ARTHUR techniques are restricted to discrete properties. Some of these techniques are quite sophisticated and have evoked great enthusiasm in the literature. The continuous property techniques in ARTHUR, on the other hand are quite familiar. This is both disappointing and reassuring. It is certainly disappointing that ARTHUR does not contain some helpful new method, but it is comforting that analysis in the past has not overlooked any useful tools. A description of all ARTHUR techniques follows.

(1) BAYES

This is a discrete category classification technique based on the application of Bayes' rule to individual features. Thus the probability that a certain pattern belongs to a particular category is estimated from the observed distribution of feature values for each category.

The ARTHUR probability that pattern i belongs to category k, based on feature j is

$$P_j\,[X_{j,k}|\,x_{i,j}] = \frac{(\mathrm{prob}_k)\,(\mathrm{risk}_k)\;P\,[x_{i,j}|X_{j,k}]}{\sum_n\,(\mathrm{prob}_n)\,(\mathrm{risk}_n)\;P\,[x_{i,j}\,|\,X_{j,n}]}$$

where $P[x_{i,j}|X_{j,n}]$ is the probability that feature j of category n will have a value of $x_{i,j}$, risk_k is the risk associated with misclassifying a pattern and prob_k is the a priori probability of a given pattern being a member of category k.

This result applies to single features only, so ARTHUR has scoring techniques for combining features,

$$P_{TOT}[X_k|x_i] = \Sigma_j (P_j\,[X_{j,k}|x_{i,j}])^{\alpha}$$

where α is arbitrary. Another alternative is

$$P_{TOT}[X_k\;x_i] = \Sigma_j\;\ln\,(P_j[X_{j,k}\;x_{i,j}])$$

Because BAYES is strictly a classification technique it is not applicable to the cratering problem. However, BAYES does have a feature which can be helpful for the continuous case. This is because the feature variables are continuous, and BAYES uses the input data base to construct probability distribution functions of the features. BAYES can be triggered to display this information in the form of printer plot histograms of the feature frequency distributions.

(2) CHANGE

This is a data handling routine which contains the machinery to add or delete features, change or merge categories, change pattern classifications, and perform quite general feature transformations. ARTHUR users at S^3 have

found the procedures required by CHANGE unwieldy and have opted to modify the ARTHUR data files directly.

(3) CORREL

This routine generates all feature-feature and feature-property correlation coefficients with confidence intervals about the correlations, and an estimate of the probability that the data could have come from uncorrelated parent populations. This routine is helpful for characterizing the data, but the confidence interval and probability of significance must be accepted with caution. These quantities are derived under the assumption of normality, and are meaningless if this condition is violated.

(4) DISTANCE

This routine calculates a "distance" matrix whose elements are the "distances" between each pattern in the training set and every other pattern. Several arbitrary measures of distance between two points in a multidimensional space are used. These definitions of distance preserve the notion of a small distance between points which have similar coordinates in multidimensional space, and a large distance between points with dissimilar coordinates.

These measures of distance lose a great deal of metric information and are essentially qualitative.

(5) DUMMY

This is a nonfunctional routine intended to allow the easy insertion of a user written special program.

(6) END

This routine is called to trigger a normal termination of an ARTHUR run.

(7) GRAB

This routine produces new features based on ordering of weighted data and correcting for correlation between features. It only partially removes intrafeature correlation. The resulting features are auto-scaled but not weighted or decorrelated. One is urged to use this routine with caution. Since this routine is a rough attempt at what is done exactly in SELECT we elected not to use it at all.

(8) HEIR

This routine uses interpattern distances as a measure of similarity and forms a graph called a "dendrogram" which illustrates the hierarchical cluster structure. This is a classification tool, and not relevant for the cratering problem. This routine did not run on our machine, and we chose to ignore it.

(9) INPUT

This is the routine which reads cards input data and creates the data file which can be read by the other ARTHUR routines. This routine also replaces missing data with average values. The routine permits quite a latitude of input specifications, but has some rigid requirements that were not clearly documented. ARTHUR's ease of use begins after successfully running INPUT. One user found it easier to create the data file directly.

(10) KARLOV

This technique forms new features from linear combinations of the old features which produce the largest spread or variance. The technique is very useful for

classification applications but can also be used for feature reduction. We believe that this technique is inappropriate for nonlinear data.

(11) KNN

This method applies to category type data and uses the interpattern distance matrix to find the ten nearest neighbors. The categories of the nearest neighbors then predict the category of the test pattern.

(12) LEAST

This is a least squares multilinear regression technique. Linear regression analysis is the universal workhorse for data analysis, and is really the best that ARTHUR has to offer for continuous properties.

For the cratering data no linear method can be completely successful until the strong nonlinear DOB dependence is removed. There is a need for a fundamental understanding of the DOB dependence for fixed material properties.

(13) MULTI

This technique is described as a multicategory linear learning machine. The technique applies to category-type data and involves an iterative construction of hyperplanes which separate each category from all other patterns.

(14) NEW

This routine is used to initiate a new data set.

(15) NLM

"Nonlinear Mapping" uses interpattern distances and constructs a plane or 3-D projection of the N dimensional data which preserves interpattern distances and thus cluster information. This technique is not restricted to category type data, but its utility for continuous data is not clear. It is claimed that KARLOV typically produced a better separation of the data.

(16) PIECE

This is a predictive technique which can be used on nonlinear data and in a sense, is the most powerful technique for continuous properties. The major drawback of this technique is that the predictions are made entirely within the context of an ARTHUR run, and the approach does not illuminate the structure of the data. We could not see how to utilize this technique in the cratering study, but feel that this technique has many potential applications.

The technique takes each pattern, finds its nearest neighbors and performs a full least squares multilinear regression on this set. The user is warned that this technique is very expensive.

(17) PLANE

This technique is characterized as a binary linear learning machine. It applies to category type data, and consists of an iterative construction of hyperplanes which separate all possible category pairs.

(18) PNN

This technique can predict discrete or continuous properties in the context of an ARTHUR run. Using the interpattern distance matrix, the nearest neighbors of a testpattern are found. Then the predicted property is taken as the arithmetic average of the property values of the nearest neighbors.

The utility of this technique is similar to PIECE

(19) SCALE

This routine creates a data file in which the data are either range scaled (minimum 0, maximum 1) or autoscaled (mean 0, variance 1).

This routine also produces a number of useful statistical characteristics of the data. The print includes for each feature:

mean
standard deviation
normalized standard deviation
minimum
maximum
range
3rd central moment (m_3)
4th central moment (m_4)
skewness ($m_3/m_2^{3/2}$)
kurtosis (m_4/m_2^2)

These simple characteristics of the data are often quite informative. The scaled data removes from the data any numerical bias due to the choice of units.

(20) SELECT

This routine produces new features which are linearly independent and ordered according to a weight. For continuous property data the weight must be correlation to property.

Like LEAST this technique is quite hopeless in the face of the nonlinear DOB dependence. In previous analyses the nonlinear DOB dependence has been partially accounted for by the use of arbitrary fitting functions, but we feel strongly that the material property sensitivity will never be quantitatively understood until the DOB dependence is better understood.

(21) SIMCA

This routine applies to category type data only. It performs a classification on the basis of pattern similarity to a principal component model of each category.

(22) STEP

This is a least squares stepwise multilinear regression technique. It applies to continuous property data and is similar to LEAST except that the most significant variables for a fit are found and only variables which make a significant contribution to the fit are included. The routine is more expensive but more likely to be successful than LEAST. STEP and LEAST both provide several measures of the quality of the fit. Using a reasonable function to remove to DOB dependence, we were not able to produce a high quality fit. Our comments on LEAST and SELECT apply here. Unless the DOB dependence can be removed with some precision, material property sensitivity is masked by the remaining DOB variation.

(23) TREE

This routine generates a minimal spanning tree, a cluster analysis technique. This is a classification technique which is not applicable to the cratering data.

(24) TUNE

This routine generates all linear quadratic and ratio combinations of the data. It generates $2n^2 + 2n$ composite features from n input features. This is a brute force attempt to find nonlinear functional relations but of course only works for these simple nonlinearities. TUNE was used with little optimism and aside from generating a large mass of paper was unimpressive.

(25) VARVAR

This is the ARTHUR automatic plotting routine. It produces plots of feature vs feature and feature vs property. The routine scales and labels automatically and can plot using the category as a plot symbol. It also features a row by row tally of the number of plots and overplots.

We found this routine to be one of ARTHUR's major assets.

(26) WEIGHT

This routine provides measures of importance of each feature for the description of the property. Of the three weightings available variance weighting and Fisher weighting are appropriate for category type data only. The third weighting option, correlation to property is only appropriate for continuous data.

III. ARTHUR ANALYSIS OF CRATERING DATA

The purpose of this study was to determine if the ARTHUR code could be used to enhance our understanding of cratering systematics with particular emphasis on the influence of material properties.

The study was confined to a data base which was compiled and analyzed by L. A. Dillon. Dillon assumed a general functional form which would be cast in linear form and obtained parameters by linear regression analysis. Dillon's approach can be successful if the data base is complete and if the data are well described by the fitting function. Choosing an appropriate data base and fitting function generally requires insight to the data base structure, and the fitting process is generally laborious.

A question addressed by this study was: Does ARTHUR contain some capability which would simplify this task In particular we wish to determine if ARTHUR contains features which simplify the analysis of the Dillon data base and could be applied to a larger data base. Our experience with ARTHUR and the Dillon data follow.

The first tests were performed with raw Dillon data. Some strong relationships were exposed by CORREL and by the plotting routine VARVAR. High correlation coefficients were produced for the following pairs of variables.

volume - yield (r = .991)
s wave speed - p wave speed (r = .998)
s wave speed - shear modulus (r = .967)
s wave speed - dry unit weight (r = .925)
p wave speed - shear modulus (r = .972)
p wave speed - dry unit weight (r .923)
shear modulus - dry unit weight (r = .949)
cohesion - unconfined compressive strength (r = .962)

Because the data are not normally distributed, these large correlation coefficients should not be interpreted as implying a linear relation between the variables. Plots are extremely useful in evaluating the validity of a linear relation. In particular it was noticed that the volume-yield correlation which is so dear to our hearts, was unduly biased by a single large yield event. A near linear relation is expected for all of the above pairs.

The next tests were performed with some derived quantities which are of more fundamental interest in cratering phenomenology. The plotting capability became the most useful tool in ARTHUR. Figure 1 displays a linear plot of the cratering efficiency (volume/yield) as a function of in-situ density. In this plot, the different materials have been identified by material category. The convention used is:

1:Alluvium
2:Basalt
3:Limestone
4:Playa
5:Rhyolite
6:Sand
7:Shale
8:Tuff

In this plot, anytime a new point should be superimposed on a previously plotted point, the over print is not executed. Rather, the rightmost two columns contain summary information in the form of "PLOT": the number of points plotted on the line, and "NOT": the number of points not plotted. Thus, the plot may not give an accurate picture of the actual point density, but the "NOT" column does indicate what to look for to complete the picture.

Figure 1 illustrates the departure of the dependence of volume vs. yield relation from linearity. Clearly the cratering efficiency is not a constant for a given material and cannot be explained by in-situ density variations alone. In fact, for a given material the

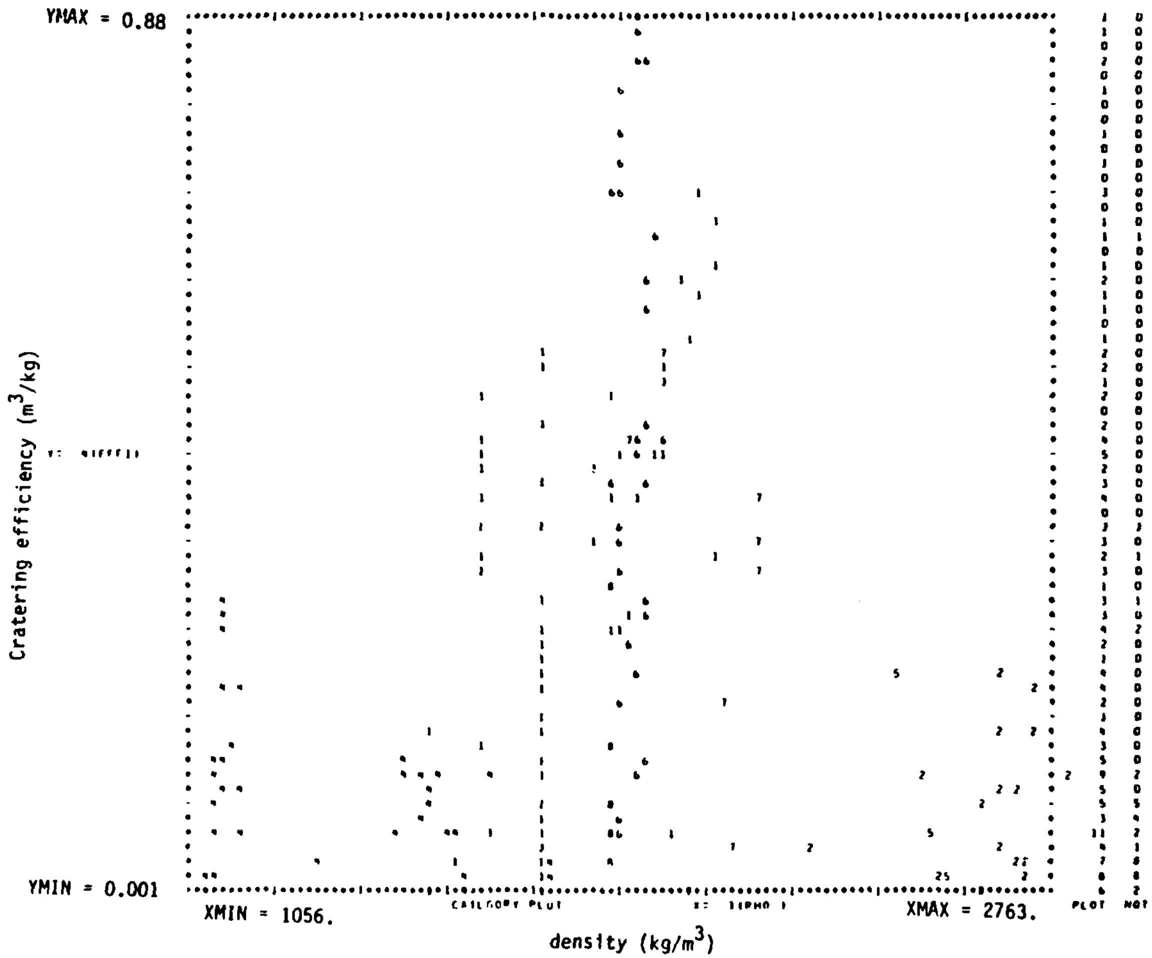

Figure 1. Cratering efficiency vs. density

variation in cratering efficiency for a given in-situ density is greater than the variation for a given material as a function of in-situ density (see alluvium, for example).

Figure 2 is a printer plot of cratering efficiency as a function of degree saturation. The degree of saturation is derived quantity which can be expressed as:

$$S = \left(\frac{\rho-\rho_d}{\rho_g-\rho_d}\right)\left(\frac{\rho_g}{\rho_w}\right)$$

where ρ = in-situ density
ρ_d = dry density of a sample
ρ_g = grain density
ρ_w = density of water

The correlation with saturation (S) for a given material is no better than that with in-situ density. This is understood when one considers Figure 3, which shows the variation of the degree of saturation as a function of in-situ density. The functional form suggests a linear dependence, and the plot reveals a nearly linear dependence within soil types. (Note that at least one value of S is anomalously large. In principle, S must be less than one. Violation of this condition is due to errors in the data.) ARTHUR automatically produced many plots of this type.

The large scatter in plots of cratering efficiency vs. material properties is explained when one considers the dependence on depth of burst. Figure 4 displays the cratering efficiency as a function of scaled depth of burst (depth of burst/volume$^{1/3}$). As expected a large cratering efficiency for some optimum value of the scaled depth of burst is shown with decreasing efficiency for greater or lesser depths of burst. The plot is poorly resolved so Figure 5 shows a transformed version of the same plot. Here the log of the cratering efficiency is plotted vs. scaled depth of burst. It is clear from this figure that the cratering efficiency increases rapidly to some optimum depth and then decreases slowly for deeper bursts. Systematic differences for the different material categories are also apparent.

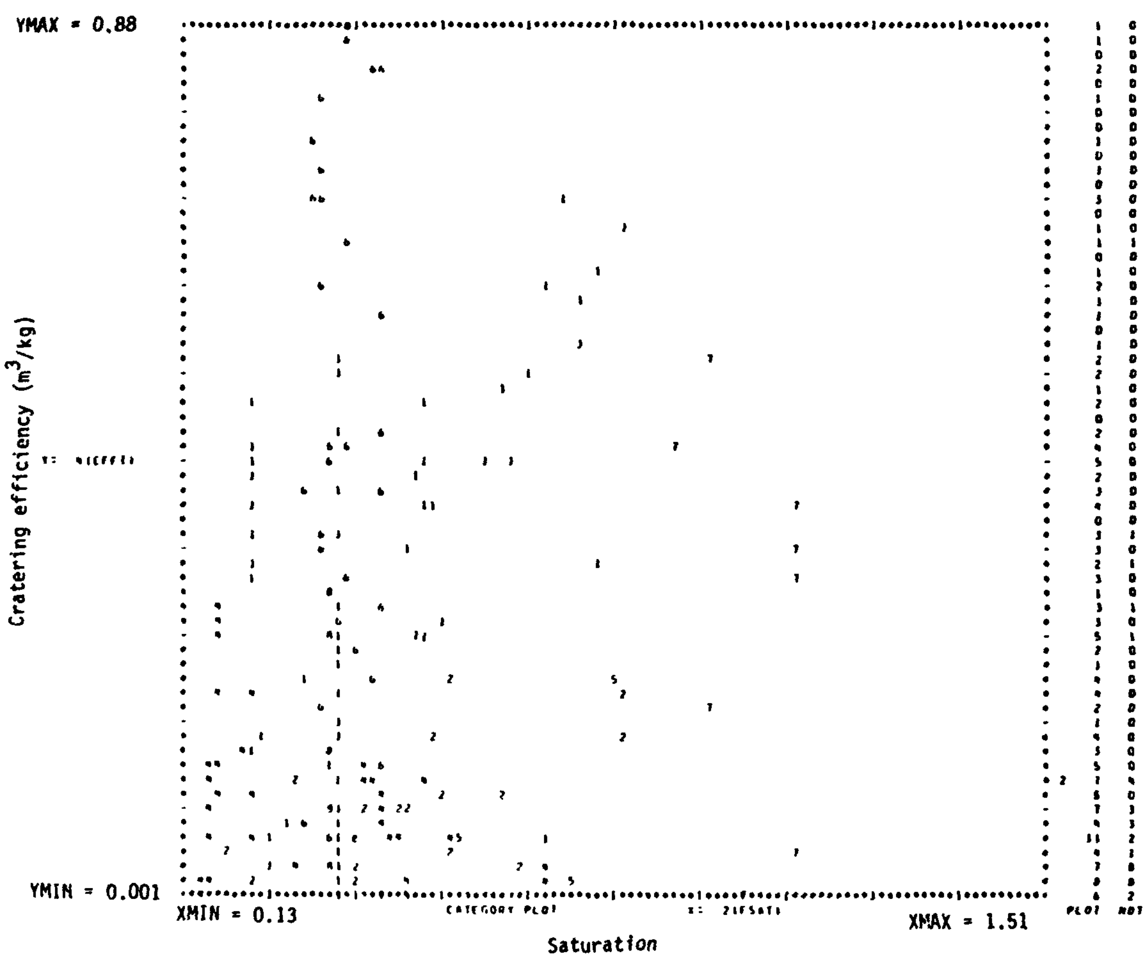

Figure 2. Cratering efficiency vs. degree of saturation

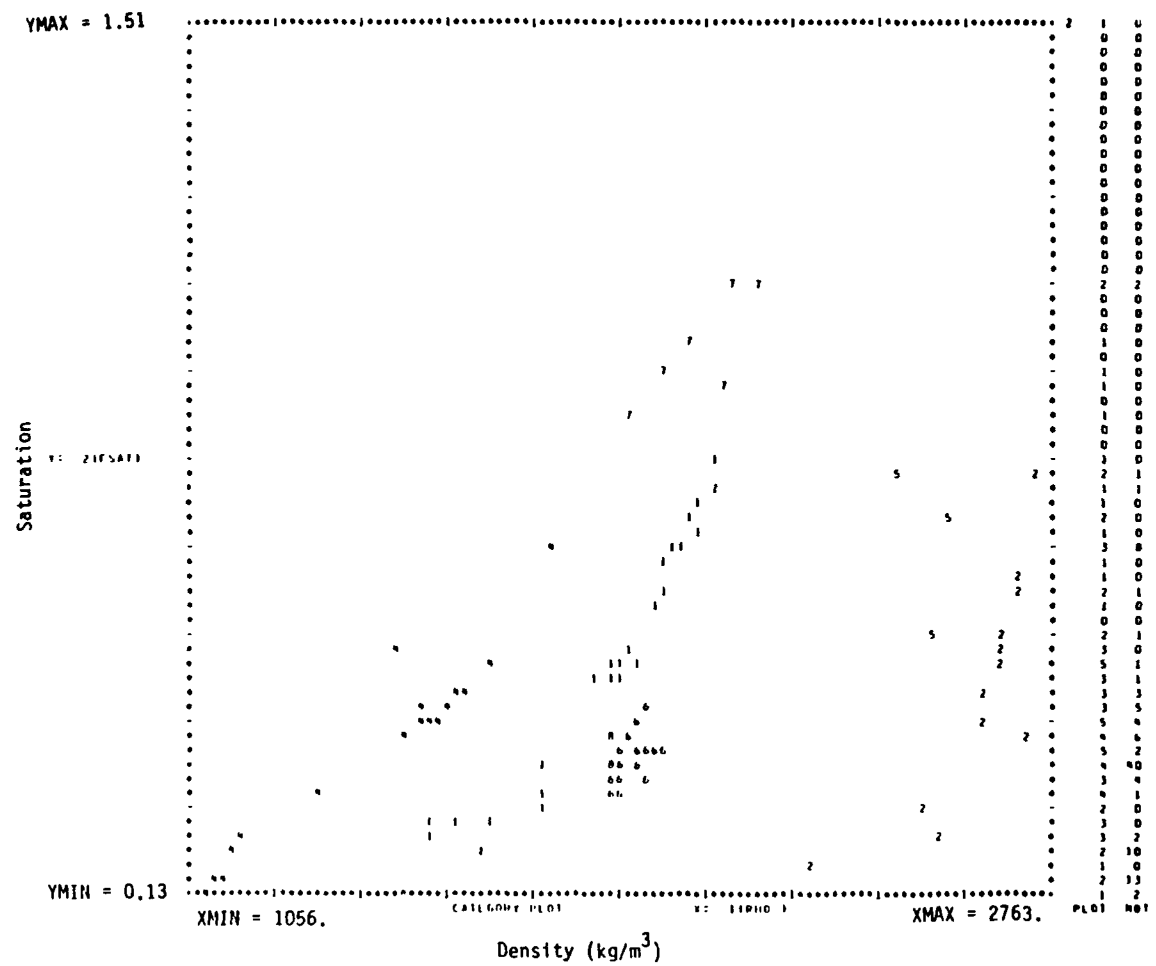

Figure 3. Degree of saturation vs. density

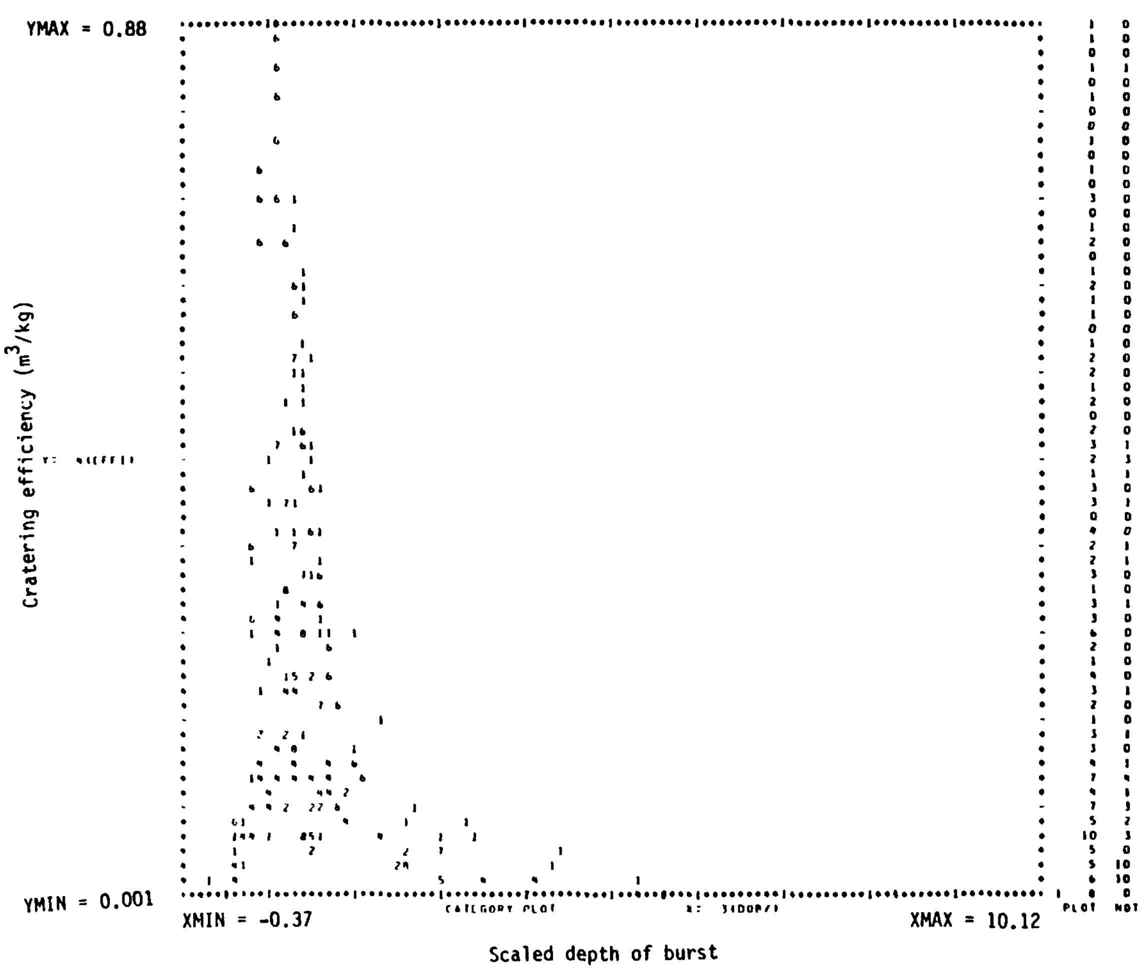

Figure 4. Cratering efficiency vs. scaled depth of burst

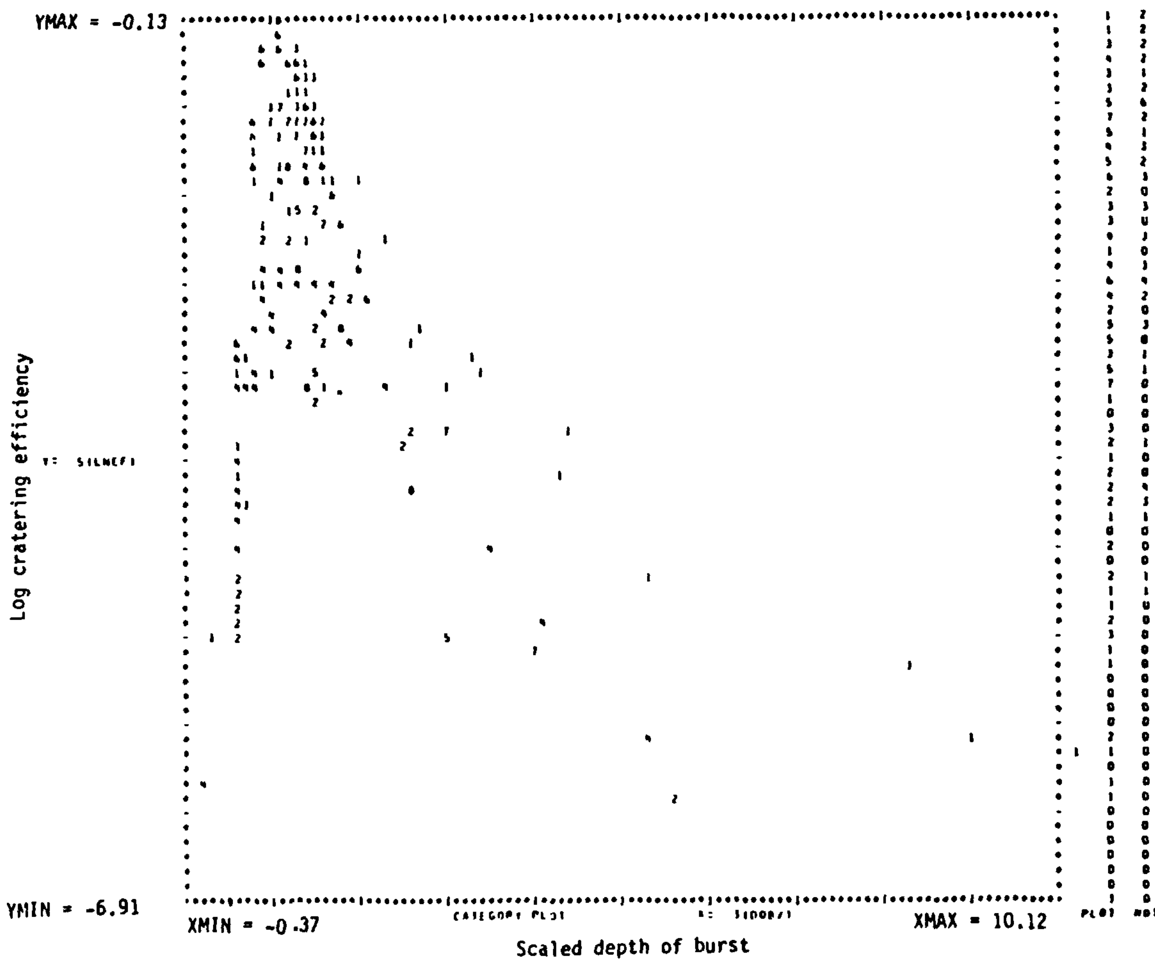

Figure 5. Log cratering efficiency *vs. scaled depth of burst*

Further reduction of the data depends on our ability to remove the depth of burst dependence so that the depth of burst variation does not overwhelm the dependence on material properties. The ARTHUR code cannot do this, and therefore this task remains the job of the researcher. Such an analysis was beyond the scope of this study, and only a modest effort was made.

Figure 6 is a high resolution plot of cratering efficiency vs. scaled depth of burst for one material - alluvium. The data are clearly not Gaussian. The rise seems exponential, and the tail falls as an inverse square. The dotted line represents an analytical model used to describe the data. The rise is hyperbolic function, and the decay is an inverse square. This form was used for a numerical exercise, and is not intended to be a general representation of cratering data.

This function was then used to scale the cratering efficiency in an ARTHUR calculation to see if the scaled (or normalized) cratering efficiency has a more systematic dependence on material properties. The plotting capability of the code was utilized again. The results were negative. This was not surprising because the original plots suggested that the optimum depth of burst was different for different materials and this was not accounted for by the fitting function.

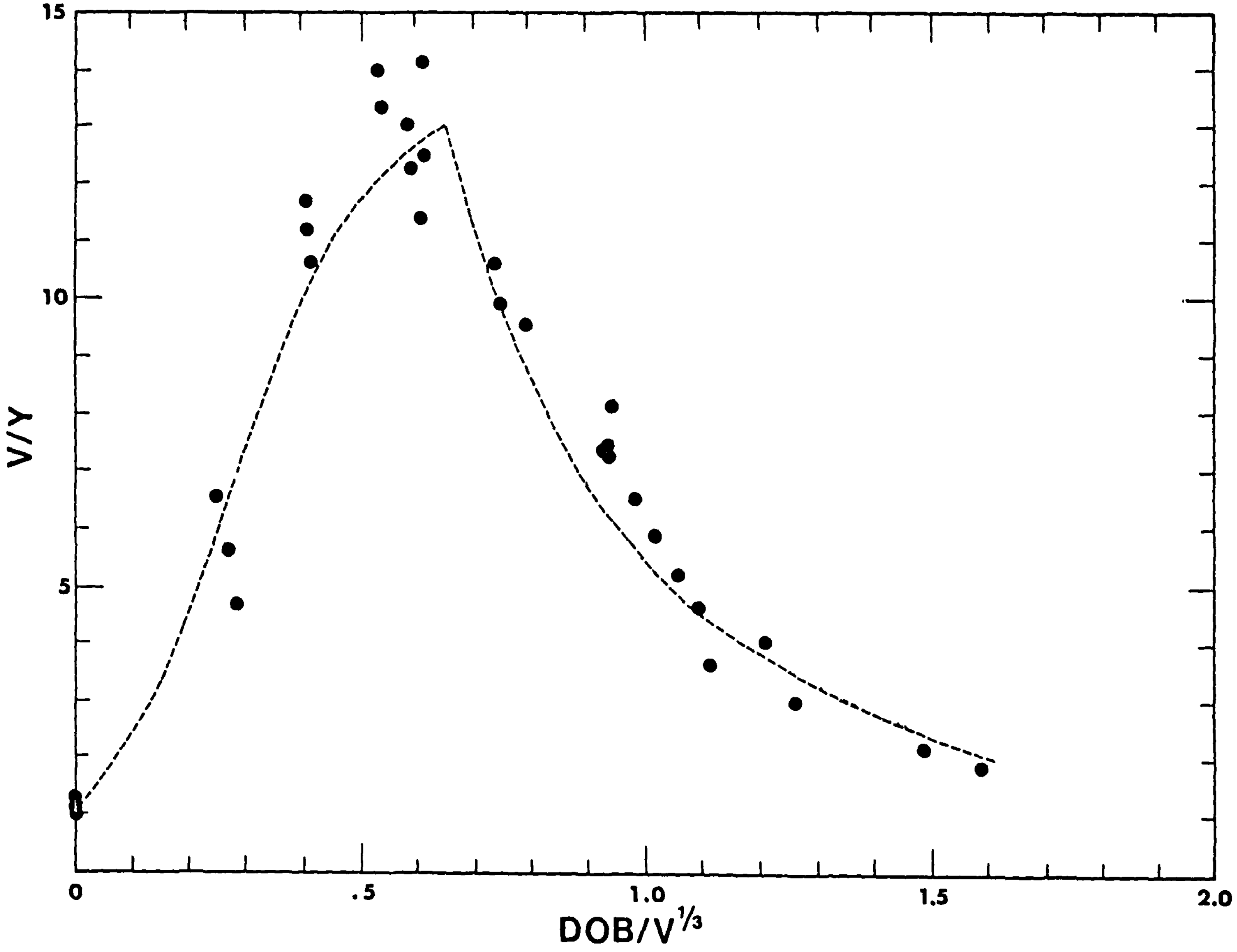

Figure 6. Cratering efficiency vs. scaled depth of burst

Discussion

The task of establishing the dependence of cratering on material properties is not eased by the ARTHUR code.

A major impediment to this analysis is the complication of the severly nonlinear depth of burst effect. While the variation due to depth of burst is much greater than the variation due to material properties, the depth of burst effect is sufficiently masked by material property variations that there is little hope of separating depth of burst effects and material property effects in a purely empirical fashion.

Another factor which makes it difficult to discriminate the effect of material properties is due to errors inherent in the material property data. One source of error is sampling error, but there is the additional problem that because of sampling bias, laboratory samples may not be representative of material in the large. In the case of strength there is the possibility of size effects, and the result of a laboratory measurement is certainly not representative material "in the large". Site charaterization is further complicated by gross variations in material properties such as layering. In this case the crater geometry does not depend on any average of the material properties, but will depend on the details of the material property variations. This last case is an instance of an uncertainty due to an important site parameter which is not present in the data base.

It is concluded that such uncertain data complicated by an unknown nonlinear depth of burst variation, presents a problem for which ARTHUR is of no particular help.

IV. ARTHUR AND THE STRENGTH OF TUFF

This section addresses an example where ARTHUR was used in a study which led to a potentially important interpretation of noisy and nonlinear data. This study was an outgrowth of work to determine the influence of material properties on the dynamics of a contained nuclear explosion. Various parameter studies have led to the conclusion that strength is the material property which most profoundly affects the final cavity configuration.

Material strength is a property which is difficult to characterize. In the DNA undergrond test program the major method of characterizing material strength is to specify the response of a sample in a uniaxial strain test. This test is relatively difficult and generally results in large sample to sample variations.

Thus, there is a strong motivation to discover some systematic dependence of strength on other, more easily measured, material properties. This question was addressed recently by R. Duff(6) at S^3. The strength parameter examined by Duff was the stress difference at 4 Kbar on uniaxial strain for 471 samples of tuff taken from various tunnel regions of area 12 at the Nevada Test Site. This strength parameter is indicative of the maximum shear stress of the tuff in a fully saturated state.

Duff attempted to find correlations between this strength parameter and other material properties using a stepwise linear regression code developed at the UCLA medical school called BMDO2R. This code has a feature like TUNE in ARTHUR, and produced a fit for which the dominant independent variable was V_S^2/ϕ where V_S is the transverse sound speed and ϕ is the porosity. However, even a fit which retained 33 compound independent variables was so poor that Duff concluded that material strength could not be reliably estimated on the basis of other conventionally determined properties.

When ARTHUR became available at S^3 Duff requested that the code be applied to the NTS strength data base. A straight forward application of the ARTHUR code basically confirmed Duff's earlier conclusion.

On the basis of this experience, it could not be concluded that ARTHUR was particularly better or worse than the other data analysis package. However, during the ARTHUR exercise some insight was gained which suggests that there may indeed be a useful correlation between strength and other material properties. This result is discussed in the remainder of this section.

In the ARTHUR analysis, the code was fully exercised. Plots, summary statistics, and multivariable fits were produced. The plots were best described as shotgun patterns, but there were some rough trends which seemed compatable with the correlation coefficients equal to -0.492 and 0.608 for strength versus porosity and strength versus shear wave speed. These are consistent with Duff's finding that the most significant compound variable was V_s^2/ϕ. However, the fit correlation was poor, and the remaining variance was not substantially smaller than the overall variance of the strength data. It was on this basis that Duff concluded that the strength of tuff could not be reliably estimated on the basis of other material properties.

When the ARTHUR study was undertaken it was observed that many strength measurements were necessary to characterize specific sites due to the large test to test variations. It became clear that at a specific site, the measured strength had a statistical distribution with a large variance, and that the goal was to predict not the outcome of an individual test, but the expected average value of the tests.

It was thus conjectured that the strength indeed had a significant dependence on V_s or ϕ which was masked by a large inherent variability. In fact strong dependences of strength on shear wave speed or porosity have been observed for the materials.

To examine this conjecture, it was decided to focus on the dependence of strength on porosity. The data were partitioned into bins containing porosity increments of ~0.02. The total range of porosities was ~0.25 to ~0.5, and a typical bin contained about forty samples. Grouping into bins was performed by sorting the ARTHUR data file, and ARTHUR runs on each of the bins produced statistical summaries which included the means and standard deviations of the strength in each bin.

The means generally decreased with increasing porosity and had a range of 23 to 75 MPa. The coefficient of variation had a range of .44 to .58. Thus the relative variation is quite uniform. An estimate of the relative error of the mean can be formed by dividing the coefficient of variation by the square root of the bin sample size. The dependence of the mean strength on porosity is shown in Figure 7. Also indicated on this figure are the probable errors of the mean strength.

The figure clearly indicates a significant dependence of strength on porosity. The precise functional form is not known, but the data are consistent with an exponential law.

This picture must be considered tentative. The correlation between strength and porosity is only useful if the remaining variance is random, and not due to uncontrolled variables. Further work should address this question by examining the coefficient of variation of the strength at specific sites.

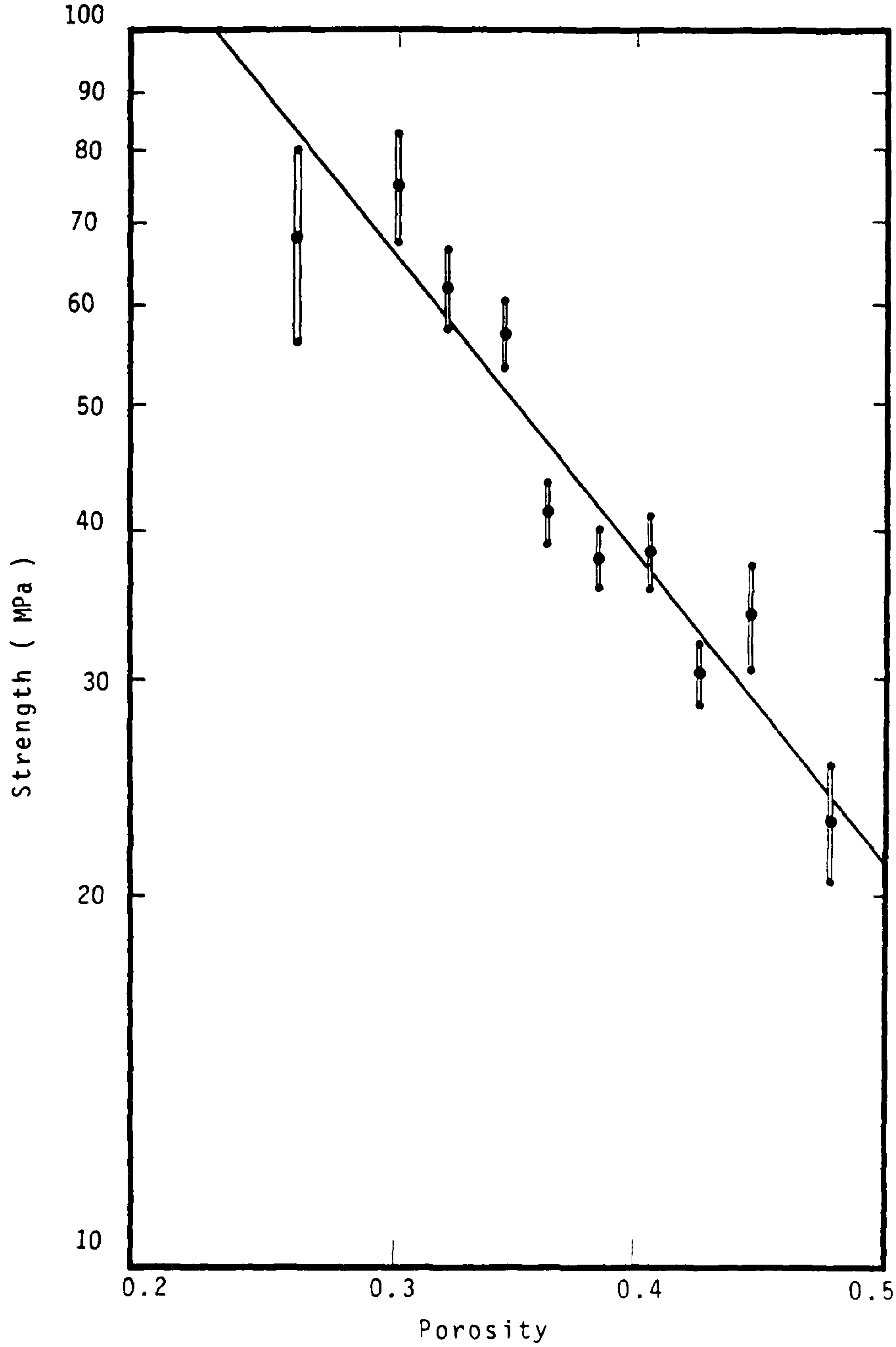

Figure 7. Mean strength versus porosity.

V. CONCLUSION

The purpose of this study was to determine if the ARTHUR code could be used to enhance our understanding of cratering systematics with particular emphasis on the influence of material properties.

The study was confined to a data base which was compiled and analyzed by L. A. Dillon. Dillon assumed a general functional form which could be cast in linear form and obtained parameters by linear regression analysis. Dillon's work represents a thoughtful and laborious effort, but the accuracy of the fit is limited by the choice of the fitting function.

The analysis could be improved if a more realistic fitting function could be found but this is a difficult task because of the complexity of the data.

A question addressed in our study was: does ARTHUR contain some capability which would simplify this task Also we ask: does ARTHUR possess *any* data analysis capability which is superior to the techniques employed by Dillon

It was determined that ARTHUR possessed no special ability to clarify the structure of multimensional nonlinear data. ARTHUR did contain versions of standard techniques which were quite comparable to those found in more conventional data analysis packages.

For continuous properties, quantitative techniques in the ARTHUR repertoire are limited to variations of conventional linear regression analysis, the same tool used by Dillon. Linear data may be analyzed by conventional (multidimensional linear) least squares analysis (LEAST), or stepwise linear regression (STEP). ARTHUR has a limited capability with non-linear data. A fruitless approach made use of TUNE which automatically forms a new feature set consisting of simple nonlinear transformations of the original

data. Analysis of the new feature set can only reveal simple nonlinear relationships. More complex nonlinear relationships can be analyzed only if specific linearizing transformations can be imposed by the user. This is the same problem that confronted Dillon.

The final quantitiative method which is available for nonlinear data is called piecewise linear regression (PIECE). With this technique, the unknown property value for some set of features is predicted by performing a stepwise linear regression for a subset of the data which lie close to the unknown point in feature space and for which the corresponding property values are known. This method uses the data to automatically predict some unknown property, but does not contribute to understanding the data.

These techniques exhaust ARTHUR's predictive capability with continuous data. Any data analysis technique adopted by pattern recognition may be equally (and perhaps primarily) claimed by conventional statistics.

Other capabilities available in ARTHUR are also not unique to pattern recognition. Statistical summary information is generated by SCALE: mean, standard deviation, minimum,, maximum, range, third and fourth moments, skewness and kurtosis. Correlation coefficients between each pair of variables are generated by CORREL. Scaled plots of each variable pair are generated by VARVAR. Histogram plots are produced BAYES.

The advantage of ARTHUR is its utility. Any number of the techniques in ARTHUR can be invoked for a single data base (or transformation of the data base) in a single run. Any routine which modifies the data has a dedicated output file which is distinct from the input file. Most routines have many run options, but will run with reasonable default values if all options are omitted.

Therefore, once the data has been input, the code can be exercised with remarkable simplicity. The following control cards will trigger the corresponding subroutines in their default modes:

```
BAYES$
CORREL$
LEAST$
STEP$
VARVAR$
SCALE$
```

Running with other options is only slightly more complicated.

Although the ARTHUR package did not contain any new tools which could be applied to the cratering systematics problem, we were favorably impressed with the code. Documentation for input and output were thorough, and the individual techniques were well referenced.

The code had a few shortcomings. Several minor bugs were found. One routine (HIER) which was not relevant for this study had serious problems which we chose not to pursue. While the output was abundant and informative, it was not exhaustive. For example, partial correlation coefficients are not displayed by the linear regression routines. The stepwise linear regression routine (STEP) had a peculiar way of deciding whether or not a variable was significant. None of these shortcomings are really serious.

It is clear that the discrete property capability of the ARTHUR code is much more powerful than the methods available for continuous properties.

The continuous property capabilities of the ARTHUR code consist of techniques that are already available to any scientist. We must conclude that ARTHUR possesses no special capability which could contribute to our understanding of cratering systematics.

APPENDIX

PATTERN RECOGNITION AND ARTHUR

Pattern recognition has been defined as a computer oriented branch of applied mathematics concerned with the detection of meaningful regularities in complex and noisy data. This field is still very young and is a logical outgrowth of automation of visual recognition tasks. The visual recognition, military photo analysis, blood cell and chromosome analysis, flaw detection, fingerprint analysis, bubble chamber event analysis, and analysis of electrocardiograms and electroencephalograms. The common problem in each of these applications is the classification of some object. Contemporary pattern recognition was born when general methods were developed which could be used in all such applications.

It should be noted that pattern recognition has a background that has been variously described as colorful and controversial. Orginally the subject included any attempt at modeling phenomena which somehow mimicked man. This included research in the areas of artifical intelligence, interactive graphic computers, computer aided design, psychological and biological pattern recognition, linguistic and structural pattern recognition, etc. (7)

Pattern recognition has emerged as a general multidisciplinary approach to data analysis with major contributions from statistics, communication theory, switching theory, control theory, operations research, biology, psychology, linguistics and computer science. It is classified as a subset of artifical intelligence. (8)

It must be pointed out that pattern recognition is not essentially different than other uses of large computers. "Pattern recognition should not be viewed as an attempt to remove the scientist from the data analysis part of experimentation. Nor,

should it be thought of as a black box within the computer that gives a machine a high degree of intelligence. Rather, it is a combination of tools that can efficiently handle the tedious task of data reduction."[9]

Nevertheless, pattern recognition carries an aura of intelligence which many authors explicitly deny. "Pattern recognition is a form of artificial intelligence which is capable of aiding the scientist in making a systematic analysis of multidimensional data. Thus, an interaction is possible between the investigator who can supply intuition and intelligence, and the computer which, by utilizing pattern recognition techniques, can recognize relationships between data in a multidimensional space."[10]

The image of intelligence is perpetuated in part by anthropomorphic terminology which is inappropriate to mathematical subject. An encyclopedia article on pattern recognition begins with an apology. "Through an abuse of language, words such as 'recognition,' and 'learning', which refer to fairly complex capabilities of humans and animals, have been applied to machine systems that implement classification and estimation algorithms. Unfortunately, this abuse of language is here to stay, and so we also will speak of 'machine recognition.'"[11]

In summary, it does not seem unreasonable to define pattern recognition as a collection of computer techniques for the analysis of abstract data.

The pattern recognition techniques used in this study are restricted to those contained in the computer package called ARTHUR. The authors of this code subscribe to the following statement of the problem addressed by pattern recognition. "Can an obscure property of a collection of objects be detected and/or predicted using indirect measurements, made on the objects, that are

known to be related to the property via some unknown relationship?"[12] Some of the terms in this statement are used a specialized sense. A pattern recognition glossary is presented in Table 2.[1] A list of the main variables in the code is given in Table 3.[1]

The generality of the approach is clear. Objects are characterized by a set of feature values and a property or category value. These feature values and property/category values are the basic input for the ARTHUR code. Once entered, a large variety of analysis methods can be invoked with impressive ease.

A summary of the methods available in ARTHUR is presented in Table 4.[10] These methods are well documented in texts such as Andrews[7] and Duda and Hart.[8]

The ARTHUR code has been successful in classification of archeological samples[13] and bond papers[14] using trace element concentration as features, classification of lunar rocks by chemical composition,[15] and classification of atomic spectra.[10] It has also been applied to material origin[16] using elemental composition, material quality[17] using chemical and physical measurements, chemical structure[18,19] using spectral measurements, and chemical or biological activity[20,21] using molecular structure and chemical composition.

Some of these investigations are essentially feasibility studies, and many involve ARTHUR principals. These studies typically exploit the discrete property capability of the code, and the results have been impressive. While no extensive literature search has been attempted, we have found no corresponding reports for the continuous property capability of the code. Our own experience with this part of the ARTHUR package is reported in the body of this report.

Table 2. A Brief Definition of Terms

The following definitions are fairly standard in the pattern recognition literature and are used in ARTHUR.

Category:	A group of patterns having the same property (generally, the value of the category is arbitrarily assigned and is not a function of the measurements). A dependent variable.
Feature:	A measurement which is transformed to enhance (hopefully) its utility in describing the data. An independent variable.
Measurement:	Any variable which can be obtained for each object.
Object:	A sample (or collection of samples considered as one) for which chemical/physical/biological/etc. measurements can be obtained.
Pattern:	The collection of measurements/features associated with one object. A point or vector in feature space.
Evaluation set:	A subset of the data not having property/categories assigned.
Property:	An assigned or measured characteristic of an object (generally, the value of the property is assumed to be a continuous function of the measurements/features). A dependent variable.
Supervised learning (pattern recognition):	Development of classification rules using patterns having known property/categories.
Test set:	A subset of the data having known property/categories used to test the predictive ability of the classification rules developed on the training set data.
Training set:	A subset of the data set having known property/categories, used to develop classification rules in supervised learining methods.
Unsupervised learning (cluster analysis; pattern recognition):	Assignment of "natural" groupings to the data without using property/category information.

Table 3. A Brief Definition of Symbols

NCAT:	The number of categories; if continuous property data, NCAT=1.
NPAT:	The number of patterns in the training set.
NTEST:	The number of patterns in the test/evaluation set.
NVAR:	The number of measurements/features.
x_i:	The vector of feature values for pattern i.
$x_{i,j}$:	Feature j of pattern i.
P_i:	The property/category of pattern i.

Table 4. Pattern Recognition Techniques in ARTHUR

METHOD (CODE NAME)	DESCRIPTION
Preprocessing	
Change (CHANGE)	Provides a variety of feature category and pattern alternations which provide flexibility in data utilization.
Karhunen-Loeve Transformation (KARLOV)	Performs the Karhunen-Loeve transformation. The transformation is an orthogonal rotation of the n-dimensional coordinate system in question, such that the first new coordinate is in the direction of largest variance and thus contains the most separating information of the data set. The second coordinate chosen is orthogonal to the first and is in the direction of the second largest variance of the data set. This process is continued until n new coordinate axes have been chosen. The transformation affords a convenient means of feature reduction if the first several coordinates chosen contain most of the varience or information of the data set.
Autoscale (SCALE)	Autoscales data. The process is similar to that used when one plots data on a two-dimensional graph. Such a process is necessary to avoid biasing results by data which may be expressed in small (or large) units and therefore be numerically quite large (small). The process transforms each feature to a mean of zero and a standard derivation of one without destroying separating information.

Table 4 (continued)

Correlation to Property Selection (SELECT)	Produces weighted features which are linearly independent and ordered according to correlation to property weight, variance weight, or Fisher weight. It provides information for selecting the best features for separation.
Tune (TUNE)	Generates all linear, quadratic and ratio combinations of original features.
Weighting (WEIGHT)	Evaluates the individual importance of each feature for the description of the property associated with the training set patterns. Three weighting functions are available: correlation to property weight, variance weight, and Fisher weight.
Utility and Measurement Analysis	
Correlation (CORREL)	Generates all feature-to-feature and feature-to-property correlations with their corresponding confidence intervals. Interfeature covariances are also given.
Distance Matrix (DISTANCE)	Calculates all interpattern distances. The following distance metrics are available: Mahalanobis, city block, and the ratio distance of Anders.
Unsupervised Learning	
Hierarchical Clustering (HIER)	Produces a dendrogram describing the hierarchical clustering (also known as Q-mode clustering) of the training set patterns. The patterns are grouped at levels of similarity, where similarity is defined from the interpattern distances.

Table 4 (continued)

Zahn Minimal Spanning (TREE)	Generates a minimal spanning tree amoung all training set patterns. A spanning tree is a connected graph containing all the training set patterns and having no closed loops. A minimal spanning tree is a spanning tree whose total length is a minimum among all possible spanning trees. Clusters (or categories) are defined by breaking links between two points which are longer than specified. Any two adjacent broken links define a cluster.
Supervised Learning	
Bayes Classification (BAYES)	Performs an approximate multivariate Bayes-rule classification. True probability distributions over each category for each feature are presumed to be unknown. Frequency histograms of the training set are used as approximation to the probability distributions. *The routine is most suitable for very large* data bases.
K Nearest Neighbors (KNN)	Predicts categories on the basis of K nearest neighbors. A pattern belongs to that category which is represented most often among its K nearest neighbors.
Least-Squares Regression (LEAST)	Performs a least-squares multilinear regression using all features, utilizing the generalized inverse method.
Multihyperplane Separation (MULTI)	Iteratively develops (n-1)-dimensional hyperplanes separating given clusters (categories) of patterns, represented in an n-dimensional space. The routine uses negative-feedback training to develop the separating surfaces. This is referred to as a linear separator.

Table 4 (continued)

Binary-Hyperplane Separation (PLANE)	Essentially the same as the multihyperplane separation method except that it is a binary classifier. It develops separating hyperplanes between two given categories at a time.
Percentage Nearest Neighbors (PNN)	Predicts categories on the basis of a given percentage of nearest neighbors. The routine is very similar to K nearest neighbors.
Stepwise Multilinear Regression (STEP)	Performs a stepwise multilinear regression. Features used in the regression are determined by thier contribution to the total of the data set.
DISPLAY METHODS	
Nonlinear Mapping (NLM)	Performs a nonlinear mapping of the training set from its original n-dimensional apce to two or three dimensional space. The routine minimizes an error function (which is a function of interpattern distances) in an attempt to preserve interpattern distances.
Plotting (VARVAR)	Provides line-printer or Calcomp plots of feature versus feature or feature versus category. It may be used to obtain plots of scaled data, weighted features or nonlinear mapping.

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